Error mitigation with Clifford quantum-circuit data

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Currently, one of the great unsolved technological questions is whether near-term quantum computers will be useful for practical applications. These noisy intermediate-scale quantum (NISQ) devices do not have enough qubits or high enough gate fidelities for fault-tolerant quantum error correction [1]. Consequently, any observable measured on a NISQ device will have limited accuracy. However, candidate applications such as quantum chemistry require chemical accuracy to beat classical methods [2, 3]. Similarly quantum approximate optimization has the potential to beat classical optimization when high accuracy is achieved [4–6].

Hence, it is widely regarded that near-term quantum advantage will only be achieved through error mitigation. Error mitigation (EM) is broadly defined as methods that reduce the impact of noise, rather than directly correct it. A prominent EM approach is to perform classical post-processing of observable expectation values. This includes the most widely used, state-of-the-art example known as zero-noise extrapolation (ZNE), which has shown great promise [7, 8]. ZNE involves collecting data at various levels of noise, achieved by stretching gate times, and using this noisy data to extrapolate an observable's expection value to the zero-noise limit [9, 10]. It has been successfully employed to correct ground-state energies for problem sizes up to 4-qubits [7, 8, 11]. In principle the method is scalable since it only adds overhead that is linear in the number of gates. However, ZNE only corrects noise up to a certain expansion order and hence it relies on the assumption of low noise levels, an assumption that could be challenged for deep, large-scale circuits.

A crucial requirement of any EM method is scalability. While it is relatively easy to develop EM methods for small qubit systems, EM methods that work effectively at the quantum supremacy scale (> 50 qubits) are much more challenging to construct. Even methods that are in principle scalable may not actually scale well in practice.

This work aims to address this issue by proposing a novel, scalable EM method that is applicable to all gate-based quantum computers. The basic idea is shown in Fig. 1. First we generate training data, of the form $\{X_i^{\text{noisy}}, X_i^{\text{exact}}\}$, where X_i^{noisy} and X_i^{exact} are the noisy and noiseless versions of an observable's expectation value of interest. The noisy values are obtained directly from the quantum computer, while the noiseless values are simulated on a classical computer. Scalability

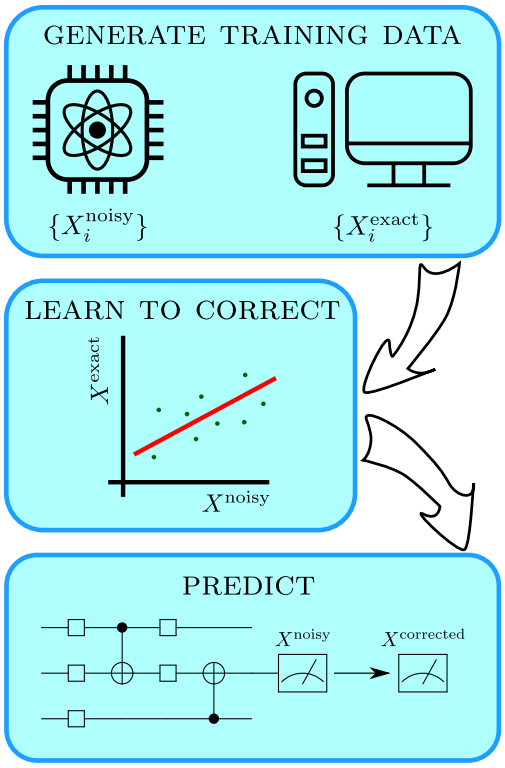

FIG. 1. Our proposed error mitigation method. For a set of states that are classically simulable, one generates noisy and corresponding noise-free data on a quantum computer and classical computer, respectively. One learns to correct on this training data by fitting the parameters of an ansatz. Finally, one uses this ansatz with the fitted parameters to predict noise-free observables for arbitrary quantum states.

is achieved by generating the training data from quantum circuits composed largely of Clifford gates (gates that map Pauli operators to Pauli operators), and hence these circuits are efficiently classically simulable. Next we fit the training data with a model, and finally we use the fitted model to predict the noise-free observable. We call our method Clifford Data Regression (CDR).

Our method is conceptually simple and could be refined with sophisticated model fitting methods offered by modern machine learning [12] and generalized by taking into account additional features like the noise level [13]. Nevertheless, even with simple linear-regression-based fitting, our method performs extremely well in practice.

A central application of error mitigation is to correct the energies of Hamiltonian eigenstates prepared on a quantum computer. Here we illustrate this application by the task of estimating the ground-state energy E of a transverse Ising spin chain defined by a Hamiltonian

$$H = -g \sum_j \sigma_X^j - \sum_{\langle j,j' \rangle} \sigma_Z^j \sigma_Z^{j'}, \tag{1}$$

where σ_X, σ_Z are Pauli operators and $\langle j, j' \rangle$ denotes a sum over nearest neighbors. We study the

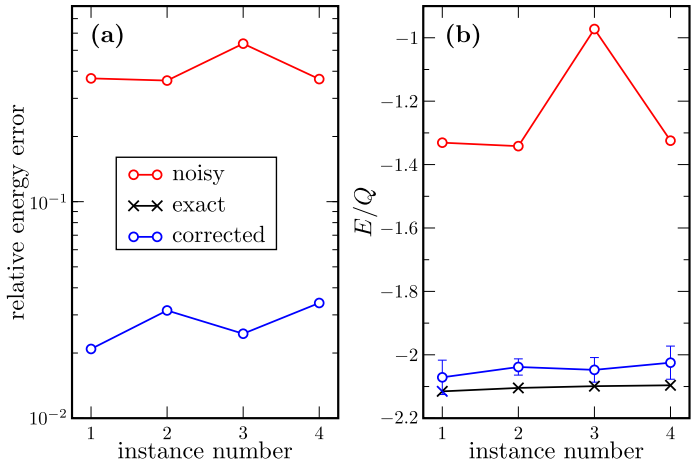

FIG. 2. Correcting local minima of the energy optimization for a 16-qubit transverse Ising model with our CDR method. We optimize a QAOA circuit with $p = 2$ ansatz layers. We perform the correction using IBM's Almaden quantum computer. (a) The relative energy error is plotted for the noisy (red) and corrected (blue) results for several optimization instances. (b) The inferred energy per qubit, E/Q, is plotted, along with the exact values (black).

case of $g = 2$. To estimate E we variationally train the Quantum Alternating Operator Ansatz (QAOA) [4, 5]. To apply the QAOA, we write $H = H_1 + H_2$ with $H_2 = -g\sum_j \sigma_X^j$ and $H_1 = -\sum_{\langle j,j'\rangle} \sigma_Z^j \sigma_Z^{j'}$. Then the QAOA is

$$\prod_{j=p,p-1\ldots,1} e^{i\beta_j H_2} e^{i\gamma_j H_1} (|+\rangle)^{\otimes Q}, \tag{2}$$

where β_j, γ_j are variational parameters, Q is the number of qubits, p is the number of ansatz layers, and $|+\rangle = (|0\rangle + |1\rangle)/\sqrt{2}$. For this task, our method reduces the error by an order-of-magnitude for a 16-qubit problem solved on IBMQ quantum computer (see Fig. 2). We find that our method appears to perform better than ZNE for this problem. Using a noise model obtained from IBM's Ourense quantum computer by get set tomography [14] we study the rate of error growth with p and Q. We find that it is not very sharp, and we still obtain order of magnitude error reductions for either $p = 4$ or 64 qubits. It is worth noting that 64 qubits is considered to be in the regime where quantum supremacy might be demonstrated [15]. We also demonstrate the utility of our method for non-variational algorithms such as quantum phase estimation.

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